웨어러블 바이오 센서를 활용한 건물 재실자 열쾌적성 감지

Assessing the feasibility of wearable-sensor-based prediction of occupant's thermal sensation

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Abstract

As of recently, information technology has become a potential means of reaching an innovative method of adjusting indoor climates, fit for the actual occupants. Among the new technological advances includes those categorized as sensing technology. Sensors have gone through rapid development to create a new field of smart IT called wearable sensors, promising accuracy and portability. These small, yet precise, wearable sensors enabled many researchers and practitioners to produce innovative methods and systems of increasing productivity, maintaining healthy and safe working environments. This new IT has been nominated as a potential outlet for resolving the issue with indoor climate systems and their lack of efficiently providing favorable indoor environments. This paper will attempt in validating this claim along with varifying the ineffectiveness of the contemporary PMV−thermostat system.

Keyword: PMV, Wearable Sensor, Machine Learning, Algorithm, Thermal Comfort, Thermal Sensation

1. Introduction

The Construction Industry, in recent years, has been greatly focused on the environmental impact the industry creates. As Darko and Chan [1] outlined, 'green buildings' have been a sort-of hotspot for many researchers and practitioners. The key factors that define GB are as follows: (1) Minimize environmental disturbances and waste generation, (2) minimize energy and other resources utilization, (3) boost renewable energy usage, and (4) improve human health and comfort. In short, while reducing the environmental impact, the occupants' satisfaction must be maintained or heightened.

While the consumption of energy and resources or the production of wastes and environmental disturbances are quantifiable, the occupants' satisfaction is not. A key, subjective feature that many researchers have participated in quantifying is human thermal comfort. ISO-7730 Predicted Mean Vote (PMV) was created to define the thermal comfort zone and is currently used in the design phase as well as the O/M phase of most buildings. However, many researchers consider this system inappropriate for properly and efficiently controlling indoor climates fit for the occupants. [2]

1.1 PMV

The PMV-based systems that are currently ubiquitous in buildings are primarily operated by a thermostat and a temperature-humidity range in which occupants are predicted to be satisfied. While this system is helpful in the passive designing of buildings as well as a means of generating a list of needed facilities, the temperature guidelines set by ISO-7730 has simply not been accurate in defining the occupants' actual comfort ranges.[2] A key fault in this system lies in the fact that real-time collection of the occupants' votes nor the clothing or metabolic rates are possible.

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1.2 Sensor–based alternative

This need for real-time input is prevalent in many fields of research within the construction industry. This common requirement has led to the adaption of new technologies that could distinguish the needs of the occupants using sensors paired with artificial intelligence to analyze the collected data. Ahn, et al. [3] outlined the various sensors and forms of data that could be collected from the respective sensors. Choi, et al. [4] has shown that physiological signals collected through a wrist-based wearable sensor could indicate the wearers' sense of risk. Implementing this strategy, this paper will attempt in bringing forth a plausible alternative that could replace the current thermostat-based climate controls by using data collected from wearable sensors.

2. Research Background

2.1 Replacing Votes

Constant occupant inputs are actions, behaviors, or even subjective, direct communication. Due to the impracticality of constantly requesting for the occupants' thermal sensations, behavioral inputs such as the activating cooling or heating units were taken as occupant inputs. [5] This study attempted to verify the temperature and humidity range in which an individual occupant would find as an acceptable indoor climate. This experiment brought forth the need to steer away from a simple averaging of past preferences, but instead a focus onto the individual occupant's preferences. This called forth a need of a system or model of input variables can be changed based on the occupant, and of outputs that were flexible enough to adjust to each and every occupant. This form of system that would focus on the actual occupants of the indoor spaces defined the concept of Personal Comfort Models. This study, however, was limited in addressing the everchanging natural conditions of typical indoors as an isolated testing chamber was used. The study also did not consider the impact of other occupants' presence affecting the indoor climate as a single individual was tested at any given time. The isolation chamber created an unrealistic environment which veers far from the naturality of actual indoor spaces.

Due to the inconclusiveness towards real-life situations, many studies have put forth experiments that were done in real spaces. Li, Menassa, and Kamat devised a method of experimentation in which the occupants' skin and core temperatures could act as indicators of the occupants' thermal sensations, potentially replacing the need for active subjective inputs. [6] To reflect the fluctuating nature of real-life scenarios, the tests were conducted in actual office spaces. While the study was capable of creating a fairly accurate prediction model that could distinguish when and how the occupant was unsatisfied with the indoor conditions, the system also neglected the impact of having multiple occupants in the same space. Another key factor that could potentially cause issues in employing the system into actual use is the fact that infrared cameras were used in the study. Not only are such cameras not portable, it is fairly a complex and expensive equipment that is incapable of capturing images over vast distances or out-of-frame.

2.2 Wearable Sensors

Recently wearable sensors have become a frequent topic in many fields of study. [3] As Awolusi and Hallowell published, wearable technologies has become an interest in the research fields for healthcare, rehabilitation, sports engineering, and other human-body related categories. [7] Wearable sensors are able to pick up small physiological changes that occur above or just below the dermal tissues of the human body. Capable of capturing and measuring kinetic, cardiac, dermal, muscular, optical, and neural activities, this new type of portable information technology (IT) could be used as indicators to the psychological state of the wearer. Following the feasibility tests that used physiological signals as indicators of risk levels, [4][3] the same could potentially applied as indicators of a wearer's thermal sensation levels.

3. Knowledge gaps and research objectives

Although 4 of the 6 criteria that are needed to estimate PMV are well quantifiable with the technology at hand, clothing factors and metabolic rates, which define the occupants' demands, are near impossible to measure in real-time. However, by incorporating sensor technology, the lack of real-time estimates of the 2 earlier mentioned parameters could be replaced with other, measurable characteristics. Such characteristics could include muscle movement, core or skin temperatures, cardiac and respiratory patterns, and other passive, physiological activities. While detailed and pinpoint accurate sensors are quite massive or require a significant amount of energy to operate, portable sensors that could be attached or worn are currently available with acceptable accuracy rates. These sensors, called wearable sensors, were proved to be capable of giving near-real-time data that could be processed and evaluated to quantify a wearer's psychological state in regards to risk. [4] Since physiological responses, if captured accurately, could be used as an indicator of risk or threat, the authors of this paper hypothesize that such relationship could be applied in regards to thermal sensations. Using various signals such as electrodermal activity (EDA), cardiac activity, and skin temperatures, a correlation between physiological responses and thermal sensations seem plausible. By finding the correlation and creating a system in which an accurate prediction of the occupant's thermal sensations, physiological-response-based climate control models could be tested and hopefully implemented in the near future.

The core objectives of this study are the following:

1: Quantify the difference between PMV and the respondents' actual votes

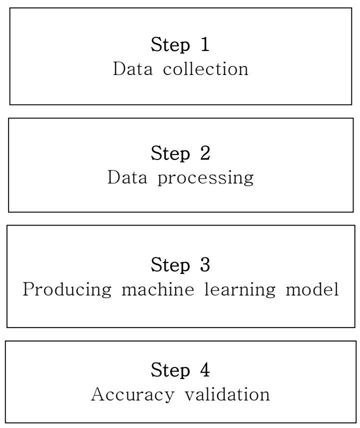
2: Produce and test various algorithm-based machine learning techniques

3: Juxtapose accuracy rates with PMV estimates to validate wearable-sensor-based prediction models

4. Research Method

4.1 Framework

The study will involve 4 major phases to complete the objectives mentioned above. The study will involve (1) collecting raw physiological and subjective data from various respondents (2) processing data to extract features and windows and shift rates to create a 50% overlap, (3) producing multiple machine learning models varying on the algorithm types, and (4) validating and comparing the accuracy rates of each model.



<Research Framework>

4.2 Testing Protocol

4.2.1 Time and Location

The data collection process was done over a 2-week period during the early-summer season (June 3- June 13) of 2020. To replicate a realistic office setting, tests were done during typical working hours of 9-16. The testing location was a small office room located in Ajou University, Suwon, South Korea. The outdoor dry-bulb temperature ranges were 18-26° C and the relative humidity ranged from 35-45%.

Due to size of the space that the experiment took place, the temperature change rates were very slow(~1° C/10minutes). As such an issue posed a problem for attaining meaningful data, the testing room was modified to a smaller size with brocade curtains that blocked from ceiling to approximately 100 meters above-floor. The windows were left as is and only change was the volume and material of one face of the testing area.

4.2.2 Respondents

Out of 27 candidates, 14(9 male and 5 female) people responded and participated in the experiment. Every respondent was in the age range of 24-30. Every participant signed a contract which stated that they understood the process and objectives of the experiment as well as the study itself, permit the collection of personal information, and agree to participate in the experiment. Each respondent was asked and confirmed whether they had any cold symptoms or health issues, including runny-nose, fever, or coughs incorporating the method done by Choi and Loftness. [8]

Subject number	1	2	3	4	5	6	7
Age	30	24	26	26	24	24	29
Sex	M	F	M	M	M	F	M
Subject number	8	9	10	11	12	13	14
Age	22	26	24	27	28	25	30
Sex	F	M	F	M	M	M	F

<table 1 : Respondent information>

4.2.3 Equipment

2 out of 3 forms of data that was collected during the experiment process were done automatically by each of the following equipment: Testo 480 and E4 wristband.

Testo 480 (by Testo) is a handheld device in which can record the dry-bulb temperature, relative and absolute humidity, mean radiant-temperature (MRT), and air flow rate. To collect these parameters, the device was connected to probes that were capable of collecting and quantifying the said parameters. To ensure that the data gathered from this device was not contaminated by noise or movement, the device was set on a stand and placed in the middle of the room, at a seated-person's head level. This device is capable of calculating the PMV values of a given room with the information collected from the probes and a set input value for the clothing and metabolic rates. Since the clothing rate varied for every respondent, every testing session had the correlating clo units applied from the ISO-7730 clo index. [9] <table 2, table 3>

E4 wristband (by Empatica) is a wearable wristband sensor that is capable of measuring EDA and skin temperatures (SKT), and gyroscopic movement and performing Photoplethysmography (PPG). The device is capable of providing clinical quality observations, streaming to a temporary cloud storage. This study utilized the EDA, PPG, and SKT sensors for data collection.<picture 1>

Testo 480	Probe	Probe name
		IAQ Probe
		Globe temperature Probe
		16mm air velocity Probe

<table 2: PMV measurement 'testo 480' with probes >

Probe	Measuring range	Accuracy
IAQ Probe	0 ~ +50℃ 0 ~ +100RH 0 ~ 10,000ppm CO_2 +700 ~ +1100hPa	±0.5℃±(1.8%RH measured value +0.7%) ±(75ppm CO_2 measured value +3%) 0 ~ +5,000ppm CO_2 ±(150ppm CO_2 measured value +5%) 5001 ~ +10,000ppm CO_2 / ± 3hpa
Globe temperature Probe	0 ~ +120℃	Maximum tolerance range: ±1.5℃
16mm air velocity Probe	+0.6 ~ +50m/s -30 ~ +140℃	±(0.2m/s measured value +1%) (0.6 ~ 40m/s) ±(0.2m/s measured value +2%) (40.1 ~ 50m/s) ±(2.5℃+measured value 0.8%)

<table 3: measuring Probes specification>
reference: testo 2020 product guide, p151

<picture 1: E4 sensors>

4.2.3 Testing Procedure

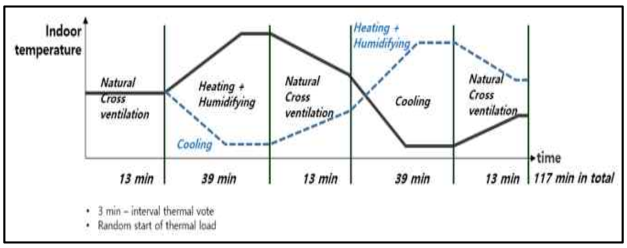
The testing cycle was approximately 130 minutes, including the explanation and contract signing procedure. The actual testing consisted about 117 minutes and during this time, the test subjects were asked to answer a survey that asked the subject's current thermal sensation every 3 minutes. As the terms 'hot', 'comfortable', and 'cold' were quite ambiguous, the approach of asking for the preferred climate change (prefer warmer, maintain current climate, prefer cooler), proposed by de Dear and Brager, was applied. [10]

(1) Prefer warner	(2) maintain current climate	(3) prefer cooler
input 1	input 2	input 3

<table 4: thermal comfort level vote comment>

During the entire session, the subject was asked to remain seated and imitate a typical office-work behavior, which ISO-7730 indexed as a 1.0 metabolic rate. [9] While giving an explanation of the study and experiment, the Testo 480 device was given the relevant inputs and activated to record the indoor climate conditions. The test subject was then asked to wear the E4 wristband. Each cycle was divided 5 phases (steady-state, heating or cooling, naturally ventilating, heating or cooling, and naturally ventilating).

The steady-state period was a 13-minute phase implemented for the occupants to thermally stabilize to the indoor climate conditions. [10] During the stead-state phase, the room was naturally ventilated with the windows, curtain, and door opened to create cross ventilation. The second phase was either a cooling or heating phase, which was randomly selected. This phase was 39 minutes long and was either cooled by an air conditioner or heated and humidified with a heater unit and a humidifier during the entire phase. The third phase was a 13-minute naturally ventilated segment that brought the indoor temperature and humidity levels down to a similar level as the outdoor conditions. This segment created set of an intermission that allowed the indoor conditions to stabilize as well as the test subject to thermally equalize with the original settings. The fourth phase was done in the similar fashion as the second phase, except the direction of which the temperature changed. For example, if the room was cooled during the second phase, it was heated during the fourth phase, vice versa. The fifth phase was a replica of the third phase, naturally ventilating the room and allowing the test subject to readjust to the outdoor temperature and humidity.<picture 2>

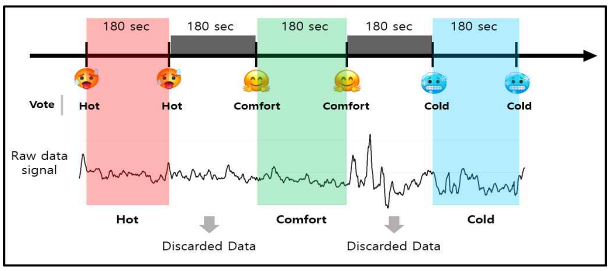


<picture 2 : indoor environment variation plan>

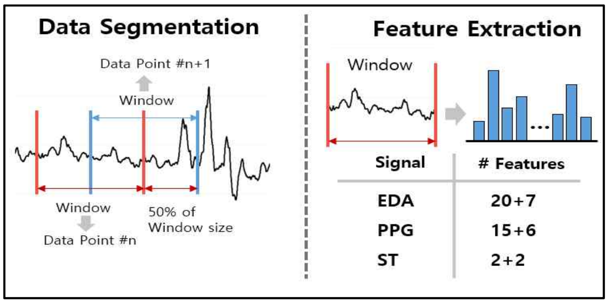
4.3 Data Processing

To proceed into the machine learning portion of the study, the raw data collected from the experiment needed to be processed. As the frequency of data being collected by each sensor and the questionnaire were different, the data needed to be matched to a set frequency, window, and shift rate. To spread the responses from the questionnaires into a 1-second frequency, a 'unanimous' vote setting was implemented. This filled the segments that had two identical responses as 180 of the same response. For cases where two immediate responses were different, the data was removed from the training and testing of the machine learning procedure. PPG, which was collected at a 64Hz frequency was grouped in to 4Hz frequency groups, maintaining only the mean, median, mode, and standard deviations. <picture 3>

The window was set as 180 seconds, or 3 minutes, to maintain the accuracy of each questionnaire response segment. These windows were set at a shift rate of 50%, which meant that 90 seconds of each frame overlapped with the previous frame. This led to a total of 3081 data sets. Each set of data consisted of 52 features (27 from Eda, 22 from PPG, and 4 from SKT), all of which were used in the study done by Choi, et al. [4] <picture 4, table 5>



< Picture 3: spreading thermal comfort vote and filtering into unanimous data>



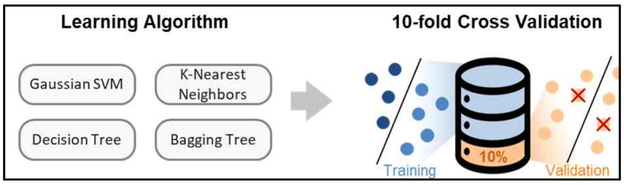
< Picture 4: feature extraction>

Signal	Feature Type	Features
EDA	Time Domain	From EDL: Mean, Standard deviation, Median, Maximum, Cumulative maximum, Cumulative minimum, Minimum-to-maximum, Peak-to-root mean square, Kurtosis, From EDR: Standard deviation, Median, Maximum, Cumulative maximum, Cumulative minimum, Minimum-to-maximum, Peak-to-root mean square, Kurtosis, Integral, Normalized average power, Normalized root mean square
	Frequency Domain	From EDL: Mean frequency, Median frequency From EDR: Mean frequency, Median frequency, Spectral power between 0.1 and 0.2 Hz, Spectral power between 0.2 and 0.3 Hz, and Spectral power between 0.3 and 0.4 Hz
PPG	Time Domain	Maximum, Cumulative maximum, Cumulative minimum, Minimum-to-maximum, Peak-to-root mean square, Kurtosis of PPG, Mean of rise time, Pulse height minimum, Pulse height maximum, Heart rate, Respiration rate, Average of NN intervals, Standard deviation of NN Intervals, Root mean square of the sequential differences of intervals, Proportion of NN intervals over 20 ms, Proportion of NN intervals over 50 ms
	Frequency Domain	Low-frequency power, High-frequency power, Low frequency to high frequency ratio, Mean frequency, Median frequency of PPG
ST	Time Domain	Mean, Standard deviation of ST
	Frequency Domain	Mean frequency, Median frequency of ST

<table 5: explanation of extracted features>

4.4 Machine Learning

The machine learning process involved using the questionnaire responses of each respondent paired with the respective, physiological data collected. Following the accuracy rates found in the study done by Choi, et al., [4] this study applied the Gaussian support vector machine (GSVM), K-nearest neighbor (KNN), Bagging tree (BT), and Decision tree (DT) algorithms. A 10-fold cross validation method was implemented to validate the accuracy ratings of each of the models. <picture 5>



<picture 5: 4 sort of machine learning algorithm adapted to prediction model with 10-fold cross validation>

5 Results

5.1 PMV Analysis

As the PMV employs a 7-point range ($-3 \le 0 \le 3$) while this study employed a 3-point range, the PMV values needed to be adjusted down to match the unit settings. The authors of this paper utilized the same method that Katic, et al. employed, which was to define 'prefer warmer' or 'cold' as $-3 \le PMV \le -0.5$, 'retain current conditions' or 'comfortable' as $-0.5 \le PMV \le 0.5$, and lastly 'prefer cooler' or 'hot' as $0.5 \le PMV \le 3$. [11] By juxtaposing this modified PMV to the actual responses that the test subjects made, the PMV yielded an accuracy rating of 66.7%.

5.2 Machine Learning Model Accuracy

The cross validation of all the machine learning models yielded the following accuracies. Of the four models, Decision tree algorithm yielded below 66.7% and thus was discarded. The remaining three outperformed in regards to accuracy, with the KNN model resulting with 87.0% accuracy rate (20.3% higher than PMV). Overall, the results showed that the machine learning models were able to predict the cases where the respondents voted 'hot' or 'prefer cooler' better than the other scenarios. The accuracy rates for predicting when the respondents were 'cold' or 'prefer warmer' were the lowest in all 4 models. This unbalanced accuracy rates are assumed to be due to the number of responses being more skewed towards the 'hot' or 'prefer cooler' votes.<table 6>

Model	(1) 'cold' accuracy	(2)'comfort' accuracy	(3) 'Hot' accuracy	Average Accuracy
GSVM	73.1%	79.6%	81.8%	79.5%
KNN	83.9%	87.1%	89.0%	87.0%
BT	65.4%	72.4%	72.6%	70.8%
PMV				66.7%

<table 6: PMV accuracy comparison to each machine learning prediction model>

6 Discussion

Although the models produced during this survey provided higher accuracy ratings that the PMV method, it is improper to proclaim that these models and wearable-sensor-based method is absolutely better. As mentioned earlier, realistic situations can vary immensely, with multiple variables that would affect occupants' thermal sensations. To reduce the number of variables, the authors of this study controlled the metabolic rates of the test subjects. The authors believe that this method of only allowing a single activity to be done during the data collection skewed the data. Thus, the models produced in this survey may be inaccurate for any settings where the test subject or occupants are not sitting down. To produce a more conclusive prediction model, a longer testing cycle time as well as various activities is needed. Another limitation that this study has is the small data pool. Due to having 52 features while only having 14 test subjects and just over 3000 data sets, it is very likely that the prediction model is 'overfit'. To compensate for this problem, more test subjects that are different from the demography of the respondents in this experiment must be present, adding a variety to the data pool. Lastly, as the data collection for this study was done during the hot and wet season, it is inconclusive as to how the models would perform during the cold and dry season. Additional data collection is required so that the model is not biasedly trained to reflect the hot and wet climates.

7 Conclusion

This study was able to perform all of the objectives laid out at the start of this research. As seen in the results, the accuracy of the models that incorporated physiological data attained by the wearable sensor are higher than that of PMV. This study was able to also prove PMV does not produce its designed 95% comfort rate. While it is too early to test the feasibility of connecting a wearable-sensor to the indoor climate control systems, it is fair to say that the data collected are able to act as indicators of the wearer' s thermal preferences.

Acknowledgement

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